

Uncertainty

Chapter 13

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(Based on slides by UW-AI faculty)

Logic vs. Probability

Symbol: $Q, R \dots$	Random variable: $Q \dots$
Boolean values: T, F	Domain: you specify e.g. {heads, tails} [1, 6]
State of the world: Assignment to $Q, R \dots Z$	Atomic event: complete specification of world: $Q \dots Z$ <ul style="list-style-type: none">• Mutually exclusive• Exhaustive
	Prior probability (aka Unconditional prob: $P(Q)$)
	Joint distribution: Prob. of every atomic event

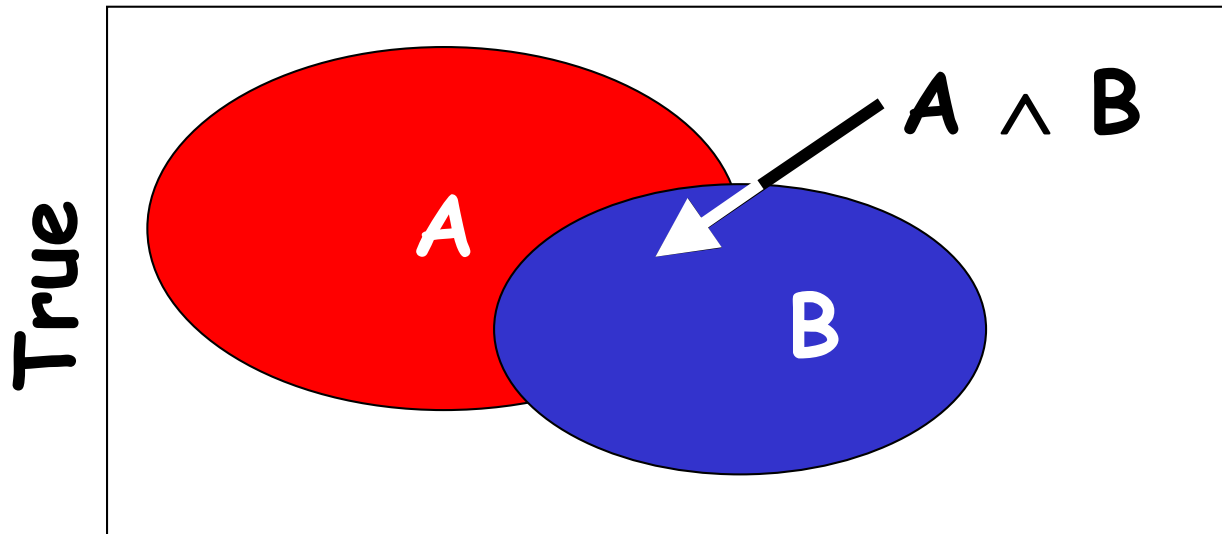
Probability Basics

- Begin with a set S : the **sample space**
 - e.g., 6 possible rolls of a die.
- $x \in S$ is a **sample point/possible world/atomic event**
- A **probability space** or **probability model** is a sample space with an assignment $P(x)$ for every x s.t.
 $0 \leq P(x) \leq 1$ and $\sum P(x) = 1$
- An **event** A is any subset of S
 - e.g. $A = \text{'die roll } < 4\text{'}$
- A **random variable** is a function from sample points to some range, e.g., the reals or Booleans

Axioms of Probability Theory

- All probabilities between 0 and 1
 - $0 \leq P(A) \leq 1$
 - $P(\text{true}) = 1$
 - $P(\text{false}) = 0$.
- The probability of disjunction is:

$$P(A \vee B) = P(A) + P(B) - P(A \wedge B)$$



Prior Probability

Prior or unconditional probabilities of propositions

e.g., $P(Cavity = true) = 0.1$ and $P(Weather = sunny) = 0.72$
correspond to belief prior to arrival of any (new) evidence

Probability distribution gives values for all possible assignments:

$P(Weather) = \langle 0.72, 0.1, 0.08, 0.1 \rangle$ (*normalized*, i.e., sums to 1)

Joint probability distribution for a set of r.v.s gives the probability of every atomic event on those r.v.s

$P(Weather, Cavity) =$ a 4×2 matrix of values:

Joint distribution can answer any question

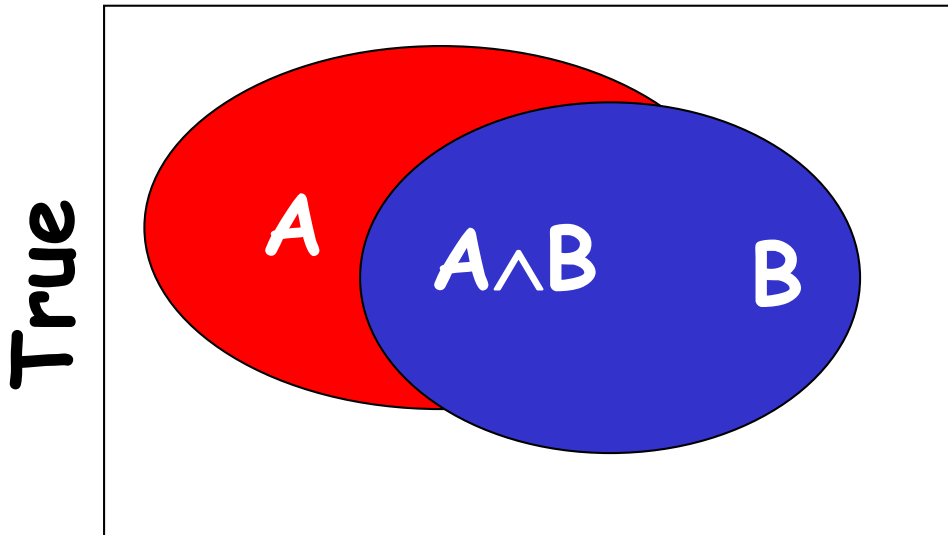
Conditional probability

- **Conditional or posterior probabilities**
e.g., $P(\text{cavity} \mid \text{toothache}) = 0.8$
i.e., given that *toothache* is all I know there is 80% chance of cavity
- Notation for conditional distributions:
 $\mathbf{P}(\text{Cavity} \mid \text{Toothache}) = 2\text{-element vector of } 2\text{-element vectors}$
- If we know more, e.g., *cavity* is also given, then we have
 $P(\text{cavity} \mid \text{toothache}, \text{cavity}) = 1$
- New evidence may be irrelevant, allowing simplification:
 $P(\text{cavity} \mid \text{toothache}, \text{sunny}) = P(\text{cavity} \mid \text{toothache}) = 0.8$
- This kind of inference, sanctioned by domain knowledge, is crucial

Conditional Probability

- $P(A | B)$ is the probability of A given B
- Assumes that B is the only info known.
- Defined by:

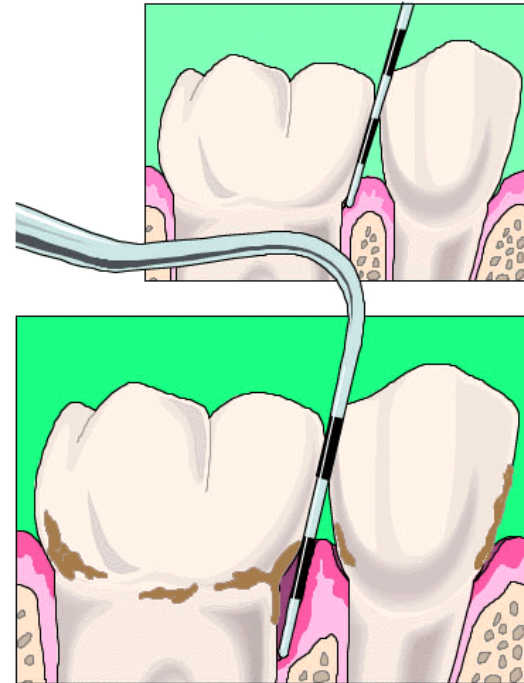
$$P(A | B) = \frac{P(A \wedge B)}{P(B)}$$



Chain Rule/Product Rule

- $$P(X_1, \dots, X_n) = P(X_n | X_1 \dots X_{n-1})P(X_{n-1} | X_1 \dots X_{n-2}) \dots P(X_1)$$
$$= \prod P(X_i | X_1, \dots, X_{i-1})$$

Dilemma at the Dentist's



What is the probability of a cavity given a toothache?
What is the probability of a cavity given the probe catches?

Inference by Enumeration

Start with the joint distribution:

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>			.072	.008
\neg <i>cavity</i>			.144	.576

For any proposition ϕ , sum the atomic events where it is true:

$$P(\phi) = \sum_{\omega: \omega \models \phi} P(\omega)$$

$$\begin{aligned} P(\text{toothache}) &= .108 + .012 + .016 + .064 \\ &= .20 \text{ or } 20\% \end{aligned}$$

Inference by Enumeration

Start with the joint distribution:

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>				
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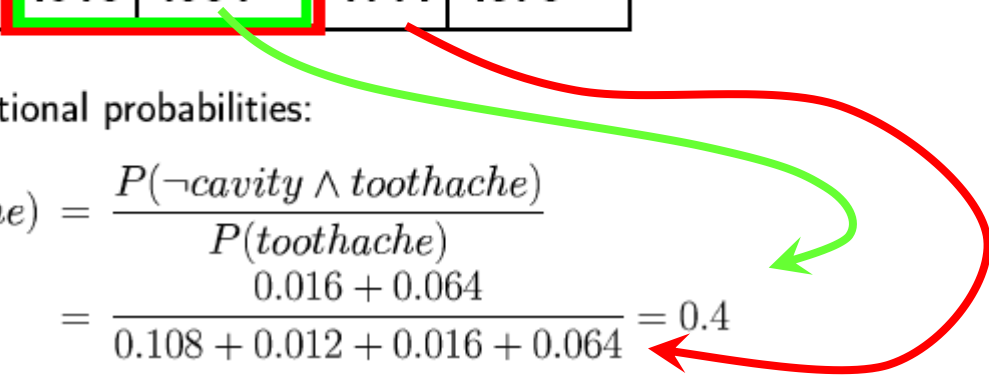
$$P(\text{toothache} \vee \text{cavity}) = .20 + .072 + .008$$
$$.28$$

Inference by Enumeration

Start with the joint distribution:

	<i>toothache</i>		\neg <i>toothache</i>	
	<i>catch</i>	\neg <i>catch</i>	<i>catch</i>	\neg <i>catch</i>
<i>cavity</i>	.108	.012	.072	.008
\neg <i>cavity</i>	.016	.064	.144	.576

Can also compute conditional probabilities:

$$\begin{aligned} P(\neg\text{cavity}|\text{toothache}) &= \frac{P(\neg\text{cavity} \wedge \text{toothache})}{P(\text{toothache})} \\ &= \frac{0.016 + 0.064}{0.108 + 0.012 + 0.016 + 0.064} = 0.4 \end{aligned}$$


Complexity of Enumeration

- Worst case time: $O(d^n)$
 - Where $d = \text{max arity}$
 - And $n = \text{number of random variables}$
- Space complexity also $O(d^n)$
 - Size of joint distribution

- Prohibitive!

Independence

- A and B are *independent* iff:

$$P(A | B) = P(A)$$

$$P(B | A) = P(B)$$



These two constraints are logically equivalent

- Therefore, if A and B are independent:

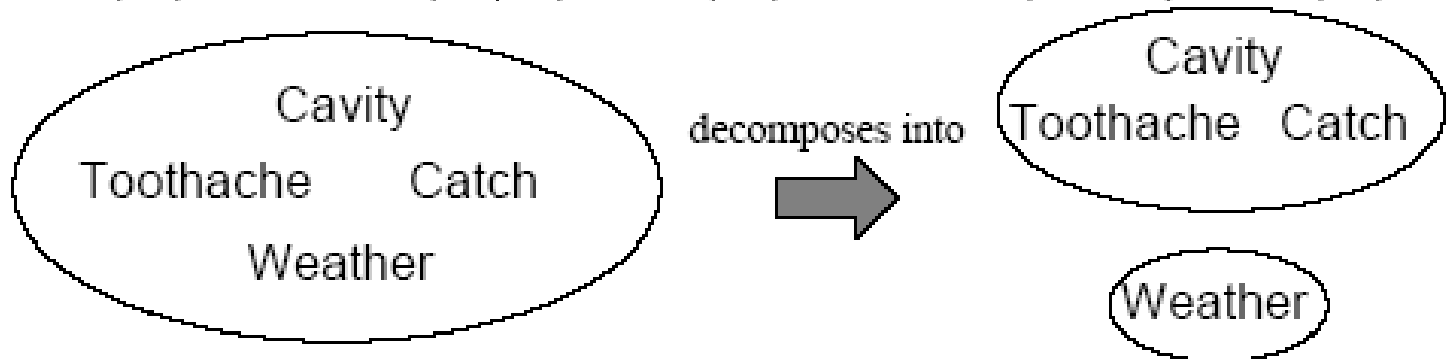
$$P(A | B) = \frac{P(A \wedge B)}{P(B)} = P(A)$$

$$P(A \wedge B) = P(A)P(B)$$

Independence

A and B are independent iff

$$\mathbf{P}(A|B) = \mathbf{P}(A) \quad \text{or} \quad \mathbf{P}(B|A) = \mathbf{P}(B) \quad \text{or} \quad \mathbf{P}(A, B) = \mathbf{P}(A)\mathbf{P}(B)$$



$$\begin{aligned} &\mathbf{P}(\textit{Toothache}, \textit{Catch}, \textit{Cavity}, \textit{Weather}) \\ &= \mathbf{P}(\textit{Toothache}, \textit{Catch}, \textit{Cavity})\mathbf{P}(\textit{Weather}) \end{aligned}$$

32 entries reduced to 12; for n independent biased coins, $2^n \rightarrow n$

Complete independence is powerful but rare
What to do if it doesn't hold?

Conditional Independence

$\mathbf{P}(\textit{Toothache}, \textit{Cavity}, \textit{Catch})$ has $2^3 - 1 = 7$ independent entries

If I have a cavity, the probability that the probe catches in it doesn't depend on whether I have a toothache:

$$(1) P(\textit{catch}|\textit{toothache}, \textit{cavity}) = P(\textit{catch}|\textit{cavity})$$

The same independence holds if I haven't got a cavity:

$$(2) P(\textit{catch}|\textit{toothache}, \neg\textit{cavity}) = P(\textit{catch}|\neg\textit{cavity})$$

Catch is **conditionally independent** of *Toothache* given *Cavity*:

$$\mathbf{P}(\textit{Catch}|\textit{Toothache}, \textit{Cavity}) = \mathbf{P}(\textit{Catch}|\textit{Cavity})$$

Instead of 7 entries, only need 5

Conditional Independence II

$$P(\text{catch} \mid \text{toothache}, \text{cavity}) = P(\text{catch} \mid \text{cavity})$$

$$P(\text{catch} \mid \text{toothache}, \neg \text{cavity}) = P(\text{catch} \mid \neg \text{cavity})$$

Equivalent statements:

$$P(\text{Toothache} \mid \text{Catch}, \text{Cavity}) = P(\text{Toothache} \mid \text{Cavity})$$

$$P(\text{Toothache}, \text{Catch} \mid \text{Cavity}) = P(\text{Toothache} \mid \text{Cavity})P(\text{Catch} \mid \text{Cavity})$$

Why only 5 entries in table?

Write out full joint distribution using chain rule:

$$P(\text{Toothache}, \text{Catch}, \text{Cavity})$$

$$= P(\text{Toothache} \mid \text{Catch}, \text{Cavity})P(\text{Catch}, \text{Cavity})$$

$$= P(\text{Toothache} \mid \text{Catch}, \text{Cavity})P(\text{Catch} \mid \text{Cavity})P(\text{Cavity})$$

$$= P(\text{Toothache} \mid \text{Cavity})P(\text{Catch} \mid \text{Cavity})P(\text{Cavity})$$

i.e., $2 + 2 + 1 = 5$ independent numbers (equations 1 and 2 remove 2)

Power of Cond. Independence

- Often, using conditional independence reduces the storage complexity of the joint distribution from exponential to linear!!
- Conditional independence is the most basic & robust form of knowledge about uncertain environments.

Bayes Rule

Bayes rules!



posterior

$$P(x, y) = P(x | y)P(y) = P(y | x)P(x)$$

$$P(x | y) = \frac{P(y | x) P(x)}{P(y)} = \frac{\text{likelihood} \cdot \text{prior}}{\text{evidence}}$$

Useful for assessing **diagnostic** probability from **causal** probability:

$$P(\text{Cause} | \text{Effect}) = \frac{P(\text{Effect} | \text{Cause}) P(\text{Cause})}{P(\text{Effect})}$$

Computing Diagnostic Prob. from Causal Prob.

$$P(\text{Cause}|\text{Effect}) = \frac{P(\text{Effect}|\text{Cause})P(\text{Cause})}{P(\text{Effect})}$$

E.g. let M be meningitis, S be stiff neck

$$P(M) = 0.0001,$$

$$P(S) = 0.1,$$

$$P(S|M) = 0.8$$

$$P(M|S) = \frac{P(s|m)P(m)}{P(s)} = \frac{0.8 \times 0.0001}{0.1} = 0.0008$$

Note: posterior probability of meningitis still very small!

Other forms of Bayes Rule

$$P(x|y) = \frac{P(y|x) P(x)}{P(y)} = \frac{\text{likelihood} \cdot \text{prior}}{\text{evidence}}$$

$$P(x|y) = \frac{P(y|x) P(x)}{\sum_x P(y|x) P(x)}$$

$$P(x|y) = \alpha P(y|x) P(x)$$

posterior \propto likelihood \cdot prior

Bayes' Rule & Cond. Independence

$$\begin{aligned} & \mathbf{P}(Cavity|toothache \wedge catch) \\ &= \alpha \mathbf{P}(toothache \wedge catch|Cavity)\mathbf{P}(Cavity) \\ &= \alpha \mathbf{P}(toothache|Cavity)\mathbf{P}(catch|Cavity)\mathbf{P}(Cavity) \end{aligned}$$

This is an example of a *naive Bayes* model:

$$\mathbf{P}(Cause, Effect_1, \dots, Effect_n) = \mathbf{P}(Cause)\prod_i \mathbf{P}(Effect_i|Cause)$$



Total number of parameters is *linear* in n